Enhancing the Self-consumption of PV-battery Systems Using a Predictive Rule-based Energy Management

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***Abstract*—A predictive real-time Energy Management System (EMS) is proposed which improves PV self-consumption and operating costs using a novel rule-based battery scheduling algorithm. The proposed EMS uses the day-ahead demand and PV generation forecasting to determine the best battery scheduling for the next day. The proposed method optimizes the use of the battery storage and extends battery lifetime by only storing the required energy by considering the forecasted day-ahead energy at peak time. The proposed EMS has been implemented in MATLAB software and using Active Office Building on the Swansea University campus as a case study. Results are compared favorably with published state-of-the-arts algorithms to demonstrate its effectiveness. Results show a saving of 20% and 41% in total energy cost over six months compared to a forecast-based EMS and to a conventional EMS, respectively. Furthermore, a reduction of 54% in the net energy exchanged with the utility by avoiding the unnecessary charge/discharge cycles.**

Keywords— Energy Management System, Battery Storage System, Renewable Energy Sources.

I. INTRODUCTION

Socioeconomic and environmental factors leads to integrate more Renewable Energy Sources (RESs) into Micro/Nano-grids (MGs/NGs) [1]. This reduces the reliance on fossil fuels and contributes to the overall power generation mix allowing energy demand to be met. RESs are inherently unreliable due to their intermittent and volatile nature [2]. Thus, government and network operators promote a self-consumption approach, aimed to reduce the load of the transmission and distribution networks. The main target of the self-consumption approach is to minimize the net energy exchanged with the utility grid necessitating the integration of Battery Storage Systems (BSSs) [3]. The self-consumption/management approach is a vital aspect of a democratized energy market, where prosumers (producers + consumers) can trade energy without using the central transmission networks.

Several control approaches are proposed in the literatures to optimize battery performance, such as computational intelligence-based algorithms. An example of this is the Ant Colony Optimization (ACO)-based and Particle Swarm Optimization (PSO)-based approaches [4]. Another PSO-based Energy Management System (EMS) for a stand-alone microturbine was proposed in [5]. In [6], the authors used PSO approach to optimize energy cost functions for a price-based EMS. Several papers have proposed off-line day-ahead scheduling, where the forecast data is fed into an off-line algorithm then combined with the real-time EMS to compensate for the forecast errors. The authors in [7] used PSO optimization to find optimal day-ahead operation settings for MG, and the mismatched power error was compensated in real-time EMS. Similarly, in [8] authors introduced mixed-integer linear programming (MILP) based EMS to find optimal day-ahead battery settings. In [9] the proposed EMS reduced operational cost by employing a dual-layer EMS, with one layer implemented via MILP and the other via a real-time controller. Although nonlinear optimization algorithms are commonly used in EMSs, they required prior knowledge of the system to tailored a cost function. Further to this, such algorithms are computationally demanding to increase the chance of converging to the global optima.

Favorable energy savings were reported in [2] using a Fuzzy Logic (FL)-based real-time EMS to optimize power flow in a MG. Over a full year, their Battery Management System (BMS) achieved a reduction in energy costs of 5.8%. This approach does however overlook the long-term effect of the unnecessary charging/discharging cycles on the battery State of Health (SOH) by not considering energy forecast. This will degrade the battery sooner, which increases the operation costs through an increase in maintenance/replacement costs of the battery. The authors in [10]offer a simple approach for the extension of battery life by limiting the State of Charge (SOC) to 50%. This approach extends battery cycles, but since it does not make the most of the battery's available capacity, it comes at the expense of a higher capital costs (for a larger battery) to achieve the required performance.

Energy forecasts have been factored into the real-time EMS proposed by several authors, such as [1, 11] where it is demonstrated the effect of energy forecasting on the battery lifetime. Their work demonstrates that storing the predicted energy only in the battery has the potential to extend the battery lifetime while reducing operating costs. Surplus stored energy is not used during off-peak period, which undermines the PV-self consumption.

This paper proposes a predictive real-time EMS which maximizes PV self-consumption and minimizes operating costs using a novel rule-based battery scheduling algorithm.

Day-ahead PV generation and demand estimation is used in the proposed EMS in order to determine the optimal battery schedule for the next day. The proposed EMS improves the use of the BSS and extends the battery lifetime by only storing the required energy according to a day-ahead forecast of energy. The proposed EMS is implemented in MATLAB software and using Swansea University's Active Office Building (AOB) as case study. This primary aspects of work contribution can be summarised as follows:

a) Integration of peak day-ahead forecasting into real-time EMS, which improves the battery's lifetime by avoiding unnecessary battery charging /discharging cycles.

b) The method reduces the energy exchanged with the utility through encouraging self-consumption, which results in a reduction of both the transmission losses as well as the requirements for central storage and generation.

c) The proposed EMS achieves a reduction in electricity bill by considering self-consumption and tariff prices.

d) Integration of a rule-based control algorithm with a day-ahead forecasting technique, leads to a fast responding time while achieving the desired results.

This paper is organized as follows. The AOB system configuration is presented in Section II, followed by proposed EMS algorithm in Section III. Section IV presents the results obtained and a comparison with the previous state-of-the-arts of [1] and [2]. Finally, the conclusion is presented in Section V.

II. THE ACTIVE OFFICE BUILDING DESCRIPTION

Fig. 1 illustrates the block diagram of the system configuration. The AOB facility employs lithium-ion battery storage of 110 kWh attached. The PV rating and maximum load power are 22.3 kW_p and 32.5 kW, respectively. The maximum battery power ($P_{b\text{-}max}$) for charge/discharge mode is +/-102.4 kW (the positive sign indicates charging mode and the negative sign is for discharging mode) [12]. Furthremore, the maximum SOC (SOC_{max}) and minimum SOC (SOC_{min}) limits are set at 98% and 20%, respectively. There are several methods are proposed in the literatures for SOC estimation such as using artificial neural networks [13], forgetting factor recursive least-squares method [14], Open-Circuit-Voltage method, and Kalman filter algorithm [15]. In this work the battery SOC is estimated at every charge/discharge cycle using the Coulomb-counting method [2]:

$$SOC\ (t) = SOC\ (0) - \frac{1}{C_{ref}\ (t)} \int_0^t P_b\ (t)\ dt \quad (1)$$

where C_{ref} is the actual battery capacity and dt is the sample time (10 min in this work), SOC (0) is the intial battery SOC, P_b represents the battery power. The new capacity is estimated by integrating the battery current I as [16]:

$$C_{ref}\ (t) = \frac{1}{SOC\ (t_\alpha)\ \text{-}\ SOC\ (t_\beta)} \int_{t\alpha}^{t\beta} I\ (t)\ \ dt \quad (2)$$

At the end of each battery cycle, the updated battery capacity is fed into (1) to estimate the new SOC based on the new capacity reference for the next cycle.

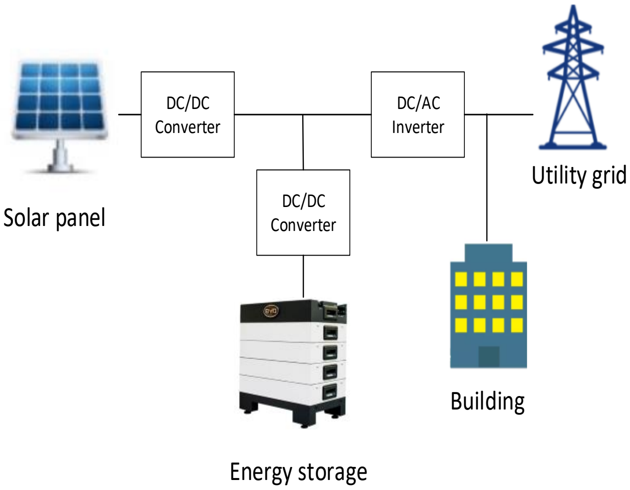


Fig. 1. Active Office Building system configuration.

III. PROPOSED EMS ALGORITHM

The proposed EMS algorithm is considered two operating modes depending on time: (A) peak or (B) off-peak. The times are selected as twelve hours according the UK energy supplier for peak and off-peak [17]. Fig. 2 illustrates the proposed real-time EMS. Figs. 3 and 4 illustrate the EMS of the peak and the off-peak times, respectively.

A. Peak time operation

If the battery SOC is less than SOC_{max} and the PV generation power (P_{PV}) is higher than demand (P_L), the PV surplus power will be used to charge the battery using (3), as shown in Fig. 3 (the black solid lines). If the battery is fully-charged (i.e., SOC > SOC_{max}), the surplus PV energy will be injected into the utility grid. This process effectively maximizes surplus PV utilization while reducing of energy exchange to and from the main utility.

$$P_b\ (t) = (P_{PV}\ (\text{t}) - P_L(\text{t})) \times \frac{(SOC_{max} - SOC\ (\text{t}))}{(SOC_{max} - SOC_{min})} \quad (3)$$

If the SOC is above SOC_{min} and the P_{PV} less than P_L, the load will be supplied by the battery during peak time using (4), as shown in Fig. 3 (the black dotted lines). If the SOC is less than or equal the SOC_{min} and the P_{PV} is less than P_L, the energy shortage will be purchased from the utility. During peak hours, the surplus PV power will be used to charge the battery, as the feed-in tariff (i.e., export power) is much lower than the import power price; this takes places regardless of off-peak forecast.

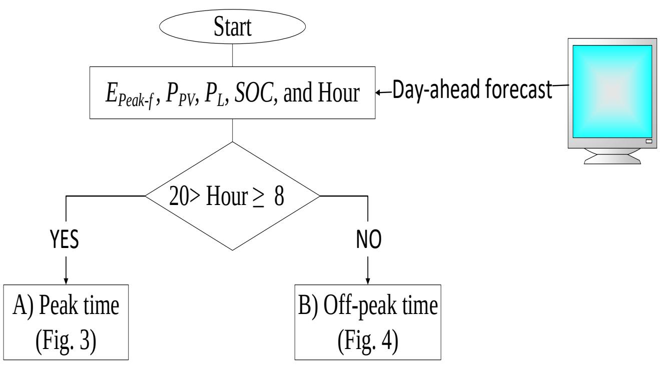


Fig. 2. The proposed real-time EMS.

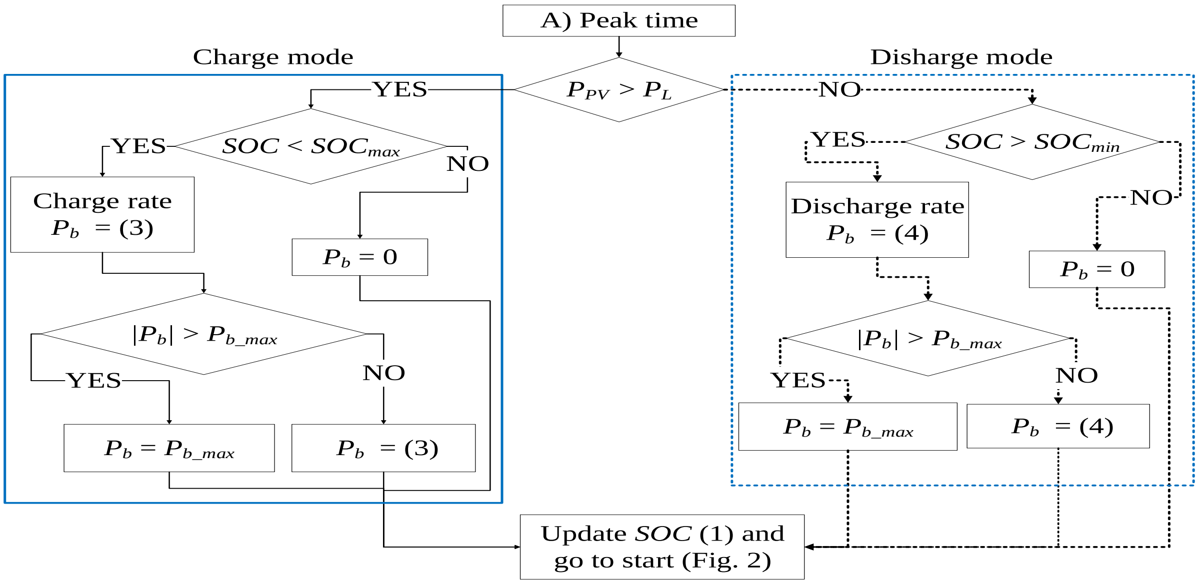


Fig. 3. The proposed peak time algorithm (A in Fig.2).

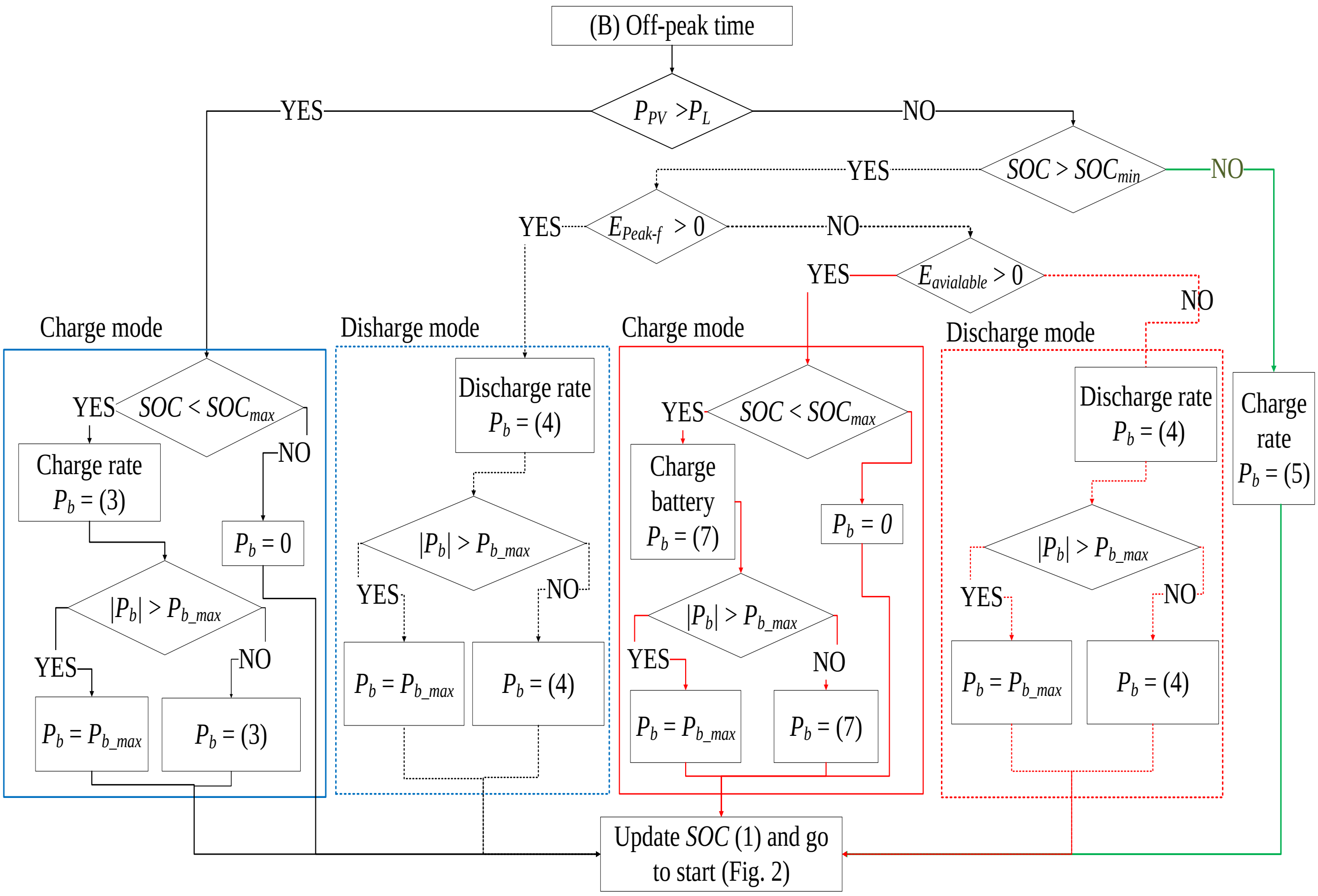


Fig. 4. The proposed off-peak time algorithm (B in Fig. 2).

$$P_b(t) = (P_{PV}(t) - P_L(t)) \times \frac{(SOC(t) - SOC_{min})}{(SOC_{max} - SOC_{min})} \quad (4)$$

Equations (3) and (4) grantee that the battery SOC will not exceed SOC_{max} and SOC_{min} during once cycle of the flowchart (i.e., 10 min).

B. *Off-peak operation*

If the *SOC* less than the SOC_{max} and the P_{PV} is higher than P_L, the surplus PV power will be used to charge the battery using (3), as shown in Fig. 4 (the solid black lines). If the battery is fully charged, the excess energy will be injected directly into the utility (P_b=0).

If the SOC less than the $\mathrm{SOC_{min}}$ and the P_{PV} is less than P_L, the battery will be charged up to $\mathrm{SOC_{min}}$ using (5), where Δt =10 min, as shown in Fig. 4 (the solid green solid lines).

$$P_b(t)=\frac{(SOC_{min}-SOC(t))\,C_{ref}(t)}{\Delta t} \tag{5}$$

The day-ahead energy forecast for the next peak time ($E_{peak\text{-}f}$) is used to determine the charge and discharge modes. If $E_{peak\text{-}f}>0$, which indicates generation is more than demand, the battery will maximize the charging from surplus PV energy during peak time, thus maximizing self-consumption during off-peak time while suppling the loads. If $E_{peak\text{-}f}<0$, which indicates demand is more than generation during the next peak time, the system will carry out a comparison between the energy stored in the battery and the forecasted energy requirement using (6). However, if the stored energy is insufficient for the next peak time (i.e. $E_{avialable}>0$), battery will be charged using (7), as shown in Fig. 4 (solid red lines). "Time" here refers to the remaining off-peak hours. If $E_{avialable}<0$, which indicates the battery has enough energy, the system will discharge (during off-peak time) this extra stored energy to supply loads using (4) as shown in Fig. 4 (the dotted red lines). This effectively ensures that the battery only stores the predicted energy required for the next peak time.

$$E_{available}(t)=\left|E_{peak\text{-}f}\right|-C_{ref}\cdot(SOC(t)-SOC_{min}) \tag{6}$$

$$P_b(t)=\frac{E_{available}}{\mathrm{Time}} \tag{7}$$

IV. Results

This study, to represent forecast data, adds the Gaussian noise to the actual PV power and load power values [1]. The Mean Absolute Percentage Error (MAPE) has been used to calculate the forecasting errors for PV and load demand powers using (8) [1]:

$$\mathrm{MAPE}=\frac{1}{\mathrm{N}}\sum_{\mathrm{to}}^{\mathrm{T}}\left|\frac{A_t-F_t}{A_t}\right|\times 100 \tag{8}$$

where F_t is the forecast, A_t is the actual point, and N represents the number of forecasts. Then, the forecasted data of PV power ($P_{PV\text{-}f}$) and load power ($P_{L\text{-}f}$) are used to calculate the total energy imbalance during peak time between the load demand and the PV source, as represented in (9). The MAPE error for PV generation and load forecast over six months period are 32% and 33%, respectively.

$$E_{peak\text{-}f}=\int_{t=8\text{ AM}}^{t=8\text{ PM}}(P_{PV\text{-}f}(t)-P_{L\text{-}f}(t))\,dt \tag{9}$$

The work presented here considers the time of energy usage into real-time EMS. The tariff prices used in this study are as follows: (a) the feed-in price for peak/off-peak time is 0.055/kWh [18], (b) the off-peak purchased price is £0.1130/kWh [17] and (c) the peak purchased price is £0.1719/kWh [17]. In this section the performance of the proposed EMS is simulated and compared with the forecast-based EMS method in [1] and a conventional EMS in [2] using MATLAB software.

A. System performance comparison

Fig. 5 compares the two-day (13th and 14th of May 2019) results of the proposed EMS with the EMS methods of [1] and [2]. The red, blue, and dashed green colours represent the SOC of this work, SOC of [1], and SOC of [2], respectively. The black colour represents the net power value (P_{PV} - P_L), which as shown, for most of the test days $P_{pv}>P_L$. Fig. 5 shows the SOC of [1] (blue line) in day 1 is maintained at 97% and in day 2 is maintained at 81% during off-peak time. Although EMS in [1], uses $E_{Peak\text{-}f}$ to store the required energy, it did not consider the surplus energy stored in the battery, which undermines a self-consumption approach and increases the operation cost.

Unlike the method of [1], the proposed method in this work uses $E_{Peak\text{-}f}$ to store only the forecasted energy during low price tariff (i.e., off-peak hours) and discharges the extra stored energy from the battery as shown in Fig. 5. In addition, the proposed method maximizes the use of PV surplus power during peak and off-peak hours as shown in Fig. 5. This process minimizes the purchase energy from utility grid by discharging the unrequired energy to supply the load.

The SOC of [2] (dashed green line), during off-peak time in days 1 and 2 battery is fully charged as shown in Fig. 5. Although energy is not needed for the next day- ahead peak hours, battery will remain fully charged. The proposed method in [2] is designed to charge the battery to full during low tariff price (i.e., off-peak hours) from the utility, so that energy can be used in high tariff price.

Fig. 6 compares another test day (10th of November 2019), when for most time $P_{pv}<P_L$. The red, blue and dashed green curves represent the SOC obtained when using the proposed EMS, EMS of [1] and EMS of [2], respectively. The black line represents the net power value (P_{PV} - P_L). As shown in Fig. 6, although battery is not required to be charged to its maximum limit (i.e., full capacity) for the next peak hours, the proposed EMS in [1] and [2], do not use the extra energy stored in the battery to supply the load during off-peak time. During peak time when load is higher than PV generation, the battery is discharged to supply load in all methods. As illustrated in Fig. 6, unlike off-peak algorithm implemented in [1] and [2], the method proposed discharges the battery to SOC (red line) of 65% by regularly comparing the available energy stored with the next peak energy. This is in accordance with the dashed black and dashed/solid red lines in Fig. 4.

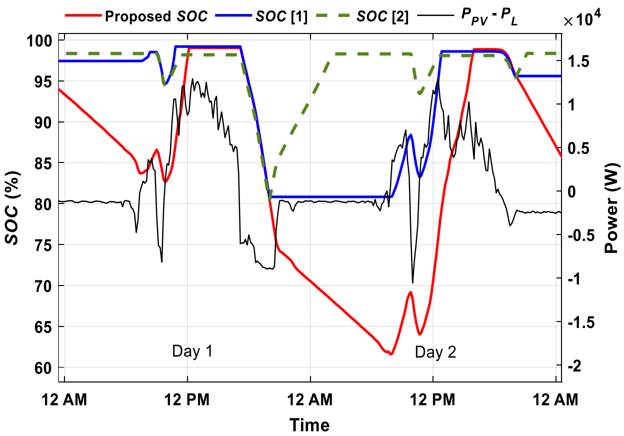


Fig. 5. Simulation results for two test days (13th and 14th of May 2019) for the EMS proposed in this work, in [1] and in [2] (shown in the red, blue and dashed green SOC curves respectively). The black line represents the net power (P_{PV} - P_L).

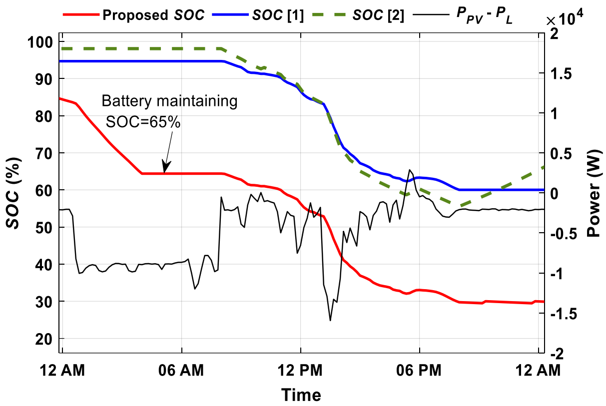


Fig. 6. Simulation results for a test day (10th of November 2019) for the proposed EMS, EMS in [1] and EMS in [2]. The red, blue and dashed green curves represent the SOC obtained when using the proposed EMS, EMS of [1] and EMS of [2], respectively. The black line represents the net power (P_{PV} - P_L).

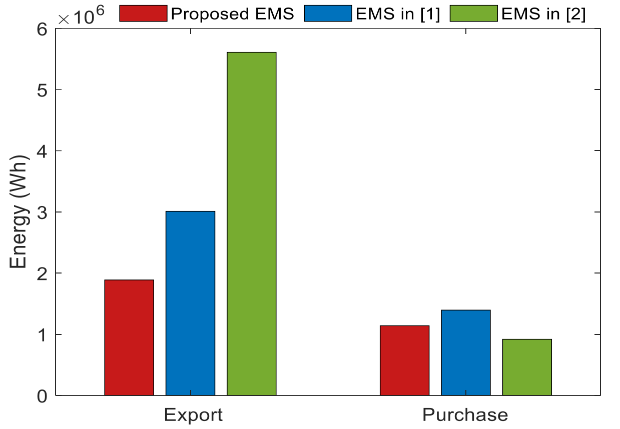
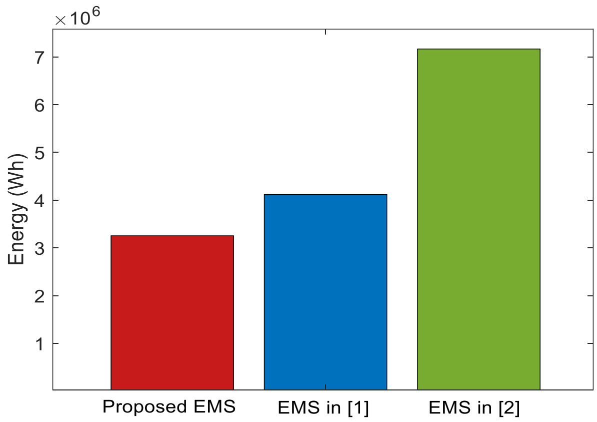


Fig. 7. Comparison of exported and purchased peak time energy (May to Oct 2019). The red, blue and green bars represent the proposed EMS, EMS in [1], and EMS in [2], respectively.



Figs. 8. Off-peak purshased energy (May to Oct 2019). The red, blue and green bars represent the proposed EMS, EMS in [1], and EMS in [2], respectively.

B. Operating costs comparison

Fig. 7 compares the total peak time exported and purchased energy using the proposed EMS with that using in [1] and [2], over the same 6 months period from May to October 2019. The EMS proposed in this work is shown in red, the EMS proposed in [1] is shown in blue and the EMS proposed in [2] is shown in green. Fig. 7 proves that the proposed method improves self-consumption by charging the battery from surplus PV power while feeding a lower amount of energy into the utility. Fig. 8 compares the total off-peak purchased energy using the proposed EMS with the proposed EMSs in [1] and [2]. Fig. 8 shows that the proposed EMS purchased less energy during low price tariff, which reduces the energy exchange with the utility by supplying the load and charging the battery based on the energy forecast during off-peak hours.

Table I compares the total costs and absolute net energy exchange with the grid using the proposed EMS with the EMSs proposed in [1] and [2] over six months. The results show that the absolute net exchanged energy is reduced by 26% and 53% compared to EMSs of [1] and [2], respectively, which will subsequently reduce the transmission losses. The net exchange energy cost is calculated as imported cost minus the exported cost. It is observed that the proposed EMS achieves a saving of 20% and 41% over six months period compared to the EMSs of [1] and [2], respectively. By minimising the amount of exchanged energy with the grid, our proposed algorithm further maximizes the PV self-consumption which is a new encouraged approach in countries such as the UK where PV penetration is relatively high.

The proposed algorithm achieves a reduction in the electricity bills via the purchase of only the estimated amount of energy at the lower tariff point while supplying the extra energy stored in the battery during off-peak times to the load.

TABLE I. COMPARING DIFFERENT ASPECTS WITH PRIVIOS STATE-OF-THE-ART

Results for six months	***Proposed EMS***	***EMS in [1]***	***EMS in [2]***
Absolute net energy exchange (kWh)	6.5×10^3	8.8×10^3	14×10^3
Net exchange energy cost (£)	564	705	967

V. CONCLUSION

A self-consumption approach is used in the proposed EMS to reduce the quantity of exchanged energy with the grid. This reduced energy exchange, in turn, reduces the requirement for central generation and storage systems as well as the transmission losses. The proposed method also reduces the operating costs through avoiding the unnecessary battery charging/discharging cycles, which improves the battery's lifetime. This is achieved by developing a simple and effective rule-based EMS that consider day-ahead energy forecast. The proposed EMS is compared with a recently published forecast-based EMS and conventional EMS to demonstrate its effectiveness. Results show a reduction in energy losses and electricity bill compared to the state-of-the-arts.

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